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CENTRAL BANKS SIGNALS AND THEIR EFFECTS IN THE FINANCIAL MARKETS – A FACTOR-AUGMENTED VECTOR AUTOREGRESSIVE MODEL APPROACH

PEDRO MIGUEL LOUREIRO ALVES – 3098

A Project carried out on the Master in Economics Program, under the supervision of:

João Valle e Azevedo

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ABSTRACT

The development of sentiment analysis enables Central Banks to better understand the impact of their formal and informal interventions in the financial markets and in the economy. This paper uses Structural VAR and Factor-Augmented VAR models, combined with a sentiment analysis developed by Kanjoya (2017), to study the impacts of the signals sent by the ECB. These models enable us to conclude that different signals sent by the Central Bank have contrasting effects in stock prices, FOREX and government debt markets. Positive signals suggest higher stock returns and lower stock volatility, whilst negative signals suggest lower returns and higher volatility.

Keywords: Sentiment Analysis, Web Content Mining, Factor-Augmented Vector Autoregressive Model, Financial Markets

INTRODUCTION

Aiming at price stability and, in some cases, full employment, currency stability or economic growth, Central Banks use financial markets as a means to achieve these goals and affect the real economy. Using short-term interest rates, and more recently some other unconventional measures, Central Banks strongly believe that they will impact market rates, asset prices, exchange rates and expectations, therefore affecting the inflation rate (The Monetary Policy Committee – Bank of England).

Providing information regarding long-term economic perspectives and goals plays an important role in the transmission mechanism, which may be even more crucial than the short-term rates targets (Sellon, 2004). By impacting the market expectations about future short-term rates, Central Banks can influence not only medium and long-term interest rates, but also exchange rates as well as stock market prices. This last mechanism can be explained by the impact of all the interest rates on the present value of future cash flows, and then on the valuation of companies, as well as on the borrowing costs, paired with the stimulative impact of the policies on the economy. In fact, easier monetary policy – i.e. lower interest rates - seems to raise stock prices (Bernanke, 2003). In what regards the exchange rate, literature has predicted that a monetary contraction causes an appreciation on the domestic exchange rate as shown by Kim and Roubini (2000), Krugman, Obstfeld and Melitz (2012) and Kim (2014).

Many studies have been conducted on the impact of monetary changes in financial markets and all of them remark monetary policy as an effective tool to affect premia and stock prices. Besides the traditional channels, Central Banks seem to be using informal mechanisms to stabilize the economy. By constantly sending signals that affect expectations, through scheduled public speaking engagements, the Central Banks may impact the stock and the foreign exchange markets.

To consider and measure these signals as well as their perception by the public, daily news articles from recognized newspapers are analyzed, using Kanjoya's (2017) lexicon to perceive the conveyed sentiments in each day. This relationship between news sentiment and stock prices has recently been receiving a lot of attention not only from economists but also from engineers because of a development of newspapers' APIs – Application Programming Interface – that enables researchers to access millions of news articles in few hours.

From more advanced computational approaches (Mittermayer, 2004 and Shumaker and Chen, 2009) to more econometric ones (Joshi, Bharathi and Rao, 2016), multiple studies have been confirming the possibility of predicting movements in the stock markets based on past performances paired with news sentiment analysis. The success of these models has been such that some Exchange-Traded Funds have been created using artificial intelligent supercomputers that trade based on economics and news data as well as historical data[1].

In a world where information is received under milliseconds, all the decisions made in financial markets are based on hundreds of different variables. Given this, and in order to make econometric inference on the effects of single shocks in the financial markets, one needs a model that enables using all possible data considered by investors.

Presented by Bernanke, Boivin and Eliasz (2004), the Factor-Augmented Autoregressive (FAVAR) model has been commonly using in economic studies as it enables the inclusion of dozens of time series into economic factors that then can be used to compute Impulse Response Functions for each time series. Commonly used to analyze monetary effects (Vargas-Silva, 2008 and Senbet, 2016), this model has already been used to test the response of exchange rates, stock markets and term spreads to impulses in the federal funds rate (Pitschner, 2013).

To measure the responses of several financial markets indices and the exchange rates to news in the Eurozone's economy, a FAVAR model is going to be followed. Using thousands news from Reuters, The Wall Street Journal and The Guardian from January 2014 to August 2017, the Kanjoya's lexicon will be used to access each day's market sentiment. Then, for each sentiment a

[1] The "Equbot with Watson AI Total US ETF" is an example of those ETFs created using this information.

different FAVAR will be made, aiming to infer whether different sentiments cause different responses in the markets.

THE MODEL

Introduced by Bernanke, Boivin, and Eliasz, (2004), the Factor-Augmented Vector Autoregressive (FAVAR) framework allows capturing the responses of a large dataset to marginal movements in an observable economic variable, Y_t. Consider a (K x 1) matrix, F_t, as a vector of unobservable factors that contains important but unobservable information not captured by the observable Y_t that cannot be expressed with a single variable, such as credit conditions and economic activity (as suggested by Bernanke et al.). The joint dynamics of F_t and Y_t are given by:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \varphi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + u_t \quad (1)$$

Where $\varphi(L)$ is conformable lag polynomial of finite order p and u_t is the error term with zero mean and a covariance matrix $\sum$.

Regressing (1) via a Vector Autoregressive (VAR) framework, even ignoring the unobservable F_t would result in biased estimators due to omitted variable bias. To solve this problem, a factor analysis used by Stock and Watson (2002) must be followed, by creating orthogonal factors through principal component analysis that influence a large variety of financial and economic variables. Let assume X_t as a large (Nx1) information matrix, in which $N > K + M$ and in which N may be greater than the number of time periods (T), as suggested by Bernanke et al.. These time series X_t are related with both Y_t and F_t.

As all the variables included in the model analyzed by this paper react contemporaneously to shocks in observable Y_t, there is no need to classify data into the two categories – "slow-moving" and "fast-moving" – as suggested by other FAVAR analysis (Bernanke et al., 2004 and Fujii et al., 2013).

DATA

To estimate the model 97 time series were considered over the period from January 1st, 2014 to August 31st, 2017. The nature of these time series can be split across two groups: the "daily words" and the financial time series.

Daily words

To measure news sentiments, thousands of online news from three news providers – Reuters, The Wall Street Journal and The Guardian – were analyzed, having all of them at least one reference to the following expressions "ECB", "European Central Bank" or "Mario Draghi". Overall, after filtering all the news for these expressions, over 21 thousand news were considered. The distribution of the news across the days considered can be found in **Figure 1**, which plots the daily number of news and the days in which the European Central Bank had official meetings. As expected the number of news regarding the Central Bank seems to peak in periods subsequent and consequent to the official meetings.

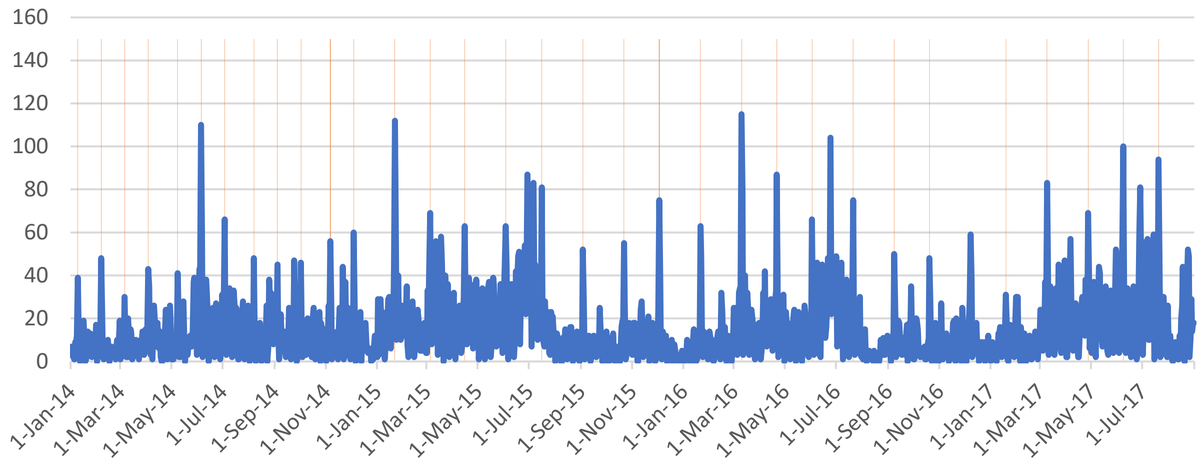

Figure 1 - Number of daily news in blue and ECB's Governing and General Councils meetings in orange

Following the extraction of the news, it was necessary to understand the sentiment behind each. To do so, the lexicon developed by Kanjoya (2017) is followed. This lexicon selects a set of words that express emotions such as confidence, positiveness or negativeness, for example – **Table 1 of the Appendix**. As millions of words needed to be considered, the daily number of words of each sentiment was computed using custom Python 2.7 codes made by the author and the libraries "urllib", "itertools", "datetime" and "time". The approach described yielded over 70000 words for the whole period considered.

The number of words paired with the number of news for each sentiment and each day enables computing a variable that aims to measure the news sentiment of each day. The variable can be written as:

$$s_{i,t} = \frac{S_{i,t}}{N_t}$$

Where i represents the sentiment, i.e. i = {negative, positive, worried, satisfied, confident, thoughtful, optimistic}, t refers to the day, S to the number of times that a word was used in the news and N the total amount of news for a given day. Overall $s_{i,t}$ is the daily number of words *per* news article that expresses a given sentiment.

Financial Time Series

To measure not only changes in the financial markets but also to get a proxy of changes in the economy, 90 financial daily time series were considered. To avoid measurement discrepancies 40 STOXX® European country and industry equity indices were studied. Besides these equities, a variety of Euro's exchange rates, government bonds, commodities and a volatility index were considered. To achieve stationarity of all the variables, the logarithmic returns of all the financial time series were computed for the variables without negative observations, and the first difference for the remaining variables.

EMPIRICAL RESULTS

Structural VAR

The vector autoregressive (VAR) model represents one of the most used time series model, mainly due to its capacity to measure the effects of shocks in one variable on other variables over time. Consider y_t as a vector of time series variables that are expected to depend on each other and on themselves across p periods. One can write a vector autoregressive model of order p, VAR(p), as:

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t$$

where A_i are parameter matrices and u_t corresponds to a white noise error vector. The equation can be rewritten as $A(L)y_t = u_t$, where the lag operator A(L) is equal to $I - A_1 L^1 - \cdots - A_p L^p$. This framework permits the estimation of the parameters through OLS and a consequent computation of the impulse response functions, which represent the over time impact of an impulse in one variable on other variables. If one assumes the error term of the VAR as structural innovations, that follow a given distribution based on some theory, then the VAR can be considered a structural VAR (SVAR). This structural autoregressive model enables the computation of impulse response functions given some short and long-run constraints.

Consider a vector $y_t = (s_{i,t}, e_t, r_t)$ where $s_{i,t}$ denotes the daily number of words *per* news article that expresses a given sentiment, e_t the percentage change in the Euro-Dollar exchange rate and r_t the EURO STOXX 50® daily returns. Following a Cholesky decomposition, which suggests that the SVAR can be written in terms of orthogonal shocks ($u = B^{-1}\varepsilon$), one imposed the following restrictions to the model:

$$\begin{bmatrix} \varepsilon_t^{s_i} \\ \varepsilon_t^{e} \\ \varepsilon_t^{r} \end{bmatrix} = \begin{bmatrix} a & 0 & 0 \\ b & d & 0 \\ c & e & f \end{bmatrix} \begin{bmatrix} u_t^1 \\ u_t^2 \\ u_t^3 \end{bmatrix},$$

where ε_t are the reduced-form errors and u_t are the structural shocks - Kilian, L. (2011). Following this system of equations, one considers shocks in the news' sentiment as exogenous, the exchange rate to respond contemporaneously to shocks in the news' sentiment and stocks revenues as being affected by shocks on both variables.

The VAR order selection was based on the Akaike Information Criterion and a lag number of 6 or 7 was found to yield the most quality for almost every sentiment, except for "worried" – tests' results can be found in **Table 2 of the Appendix**. The choice of the Akaike Information Criteria follows the results achieved by Ozcicek and McMilin (1999).

Figure 2 presents the structural VAR impulse response functions, for an impulse of one unit in the sentiment variable, i.e. for an extra word *per* news article. As expected, a positive shock in the positive, confident and optimistic news seems to have an immediate positive effect in stocks returns of *circa* 5 basis points. However, while the effect of optimistic and confident news appears to cause a longstanding positive effect, the effect from positive news seem to have close to zero effect after the first day.

On the other hand, negative signals suggest prolonged negative effects in the EURO STOXX 50 returns that peak negative 15 basis points after the third day, whilst satisfied and thoughtful news seem to impact negatively these returns in the first days, rebounding this effect after the fourth day. The first puzzling result concerns the "worried" news that apparently cause an increase in the index returns.

In what regards exchange rates the results seem to be less clear than the stock market's ones. While the exchange rate seems to appreciate initially with positive, satisfied and thoughtful news by 1, 2.5 and 1 basis points respectively, the opposite response is expected to happen to worried, confident and optimistic revelations. Even though the initial impact appears to differ across sentiments, after the fourth day all of the impulses cause a drop in the currency. Further, negative news articles appear cause a quick depreciation of the Euro currency, in the first two weeks, except for day four and five – one week after. This predicted path for the exchange rate follows Hardouvelis (1988) findings as positive news can be seen as positive expected developments that affect the future expected real interest rate, and thus the exchange rate. At the same time this positive news may be interpreted as an increase in future policy interest rates that cause an instantaneous appreciation of the currency as stated by Kearns and Manners (2006).

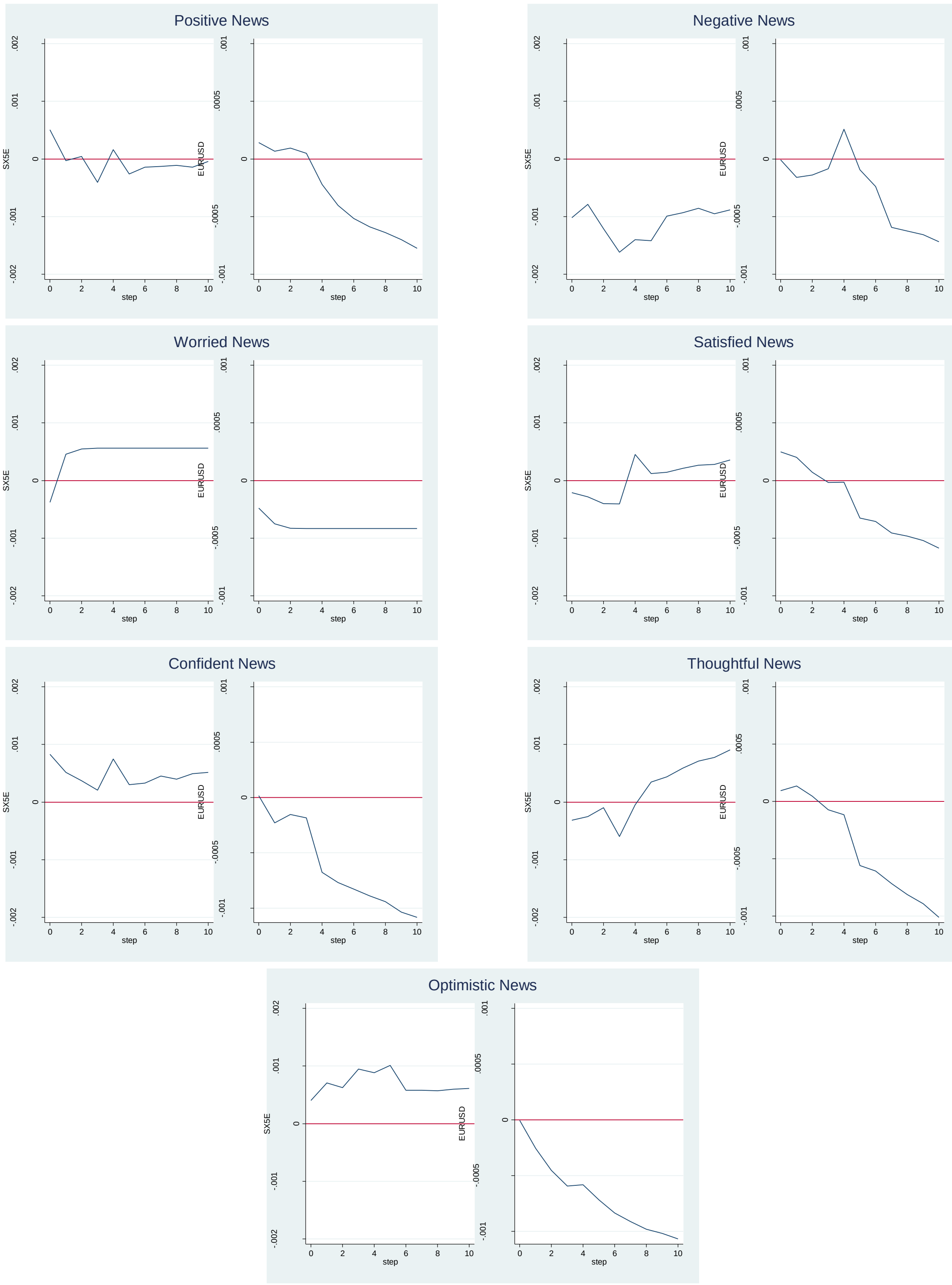

Figure 2 - EURO STOXX50 and EUR-USD - Structural VAR Impulse Response Functions. The red line denotes the y=0.

Structural VAR with One Factor

The computation of factors using dozens of time series enables considering unobserved forces in the economy and in the financial markets, such as expectations about future moves by the European Central Bank. By including a factor in the model, one expects to reduce possible endogeneity caused by omitted variable bias, as the variables included in the model react to hundreds of others.

The computation of the factors follows Stock and Watson (1998) analysis of using principal component analysis (pca) to capture non-measurable forces and use all the time series available with the exception of the ones used in the VAR. In this analysis, as over 85% of the variance could be explained by a single factor, only one factor will be introduced in the SVAR. Also, as expected given the stationarity of their components, the factor appears to be stationary.

Given this, as all the time series included in the factor are assumed to react to news announcements and articles, the vector autoregressive model acknowledges that the factor - F_t - respond to shocks in the news sentiment, such that one has:

$$\begin{bmatrix} \varepsilon_t^{s_i} \\ \varepsilon_t^{f} \\ \varepsilon_t^{e} \\ \varepsilon_t^{r} \end{bmatrix} = \begin{bmatrix} a & 0 & 0 & 0 \\ b & e & 0 & 0 \\ c & f & h & 0 \\ d & g & i & j \end{bmatrix} \begin{bmatrix} u_t^1 \\ u_t^2 \\ u_t^3 \\ u_t^4 \end{bmatrix},$$

The Cholesky decomposition considered in this case follows a similar reasoning to the one presented for the SVAR without a factor and it assumes that exchange rates and then the EURO STOXX 50® react contemporaneously not only to the news, but also to the unobservable forces.

Following the same criterion as for the structural vector autoregressive model without a factor and as a new variable is added to the model, the one factor factor-augmented vector autoregressive models were computed using a different lag for almost all the sentiments. The Akaike's criterion suggested a 1-lagged model for worried and satisfied news, 3-lagged model for positive news, 5 for negative and thoughtful signals and 6 for confident and optimistic news.

As expected, the computation of the SVAR with one factor does not change drastically the conclusions achieved by the first structural VAR – **Figure 3 -**, at least for the first days that follow the reported news. However, the introduction of one factor in the Vector Autoregressive model for negative news articles dissolves the puzzle regarding the effect of negative news on the exchange rate. Previously negative news articles appeared to cause appreciation of the currency after one week, however, by adding the one extra factor to the model, this effect seems to disappear, as a one-unit increase in $s_{negative}$ appears to drop the exchange rate by 2.5 basis points in the first day and to have a null impact after the first week.

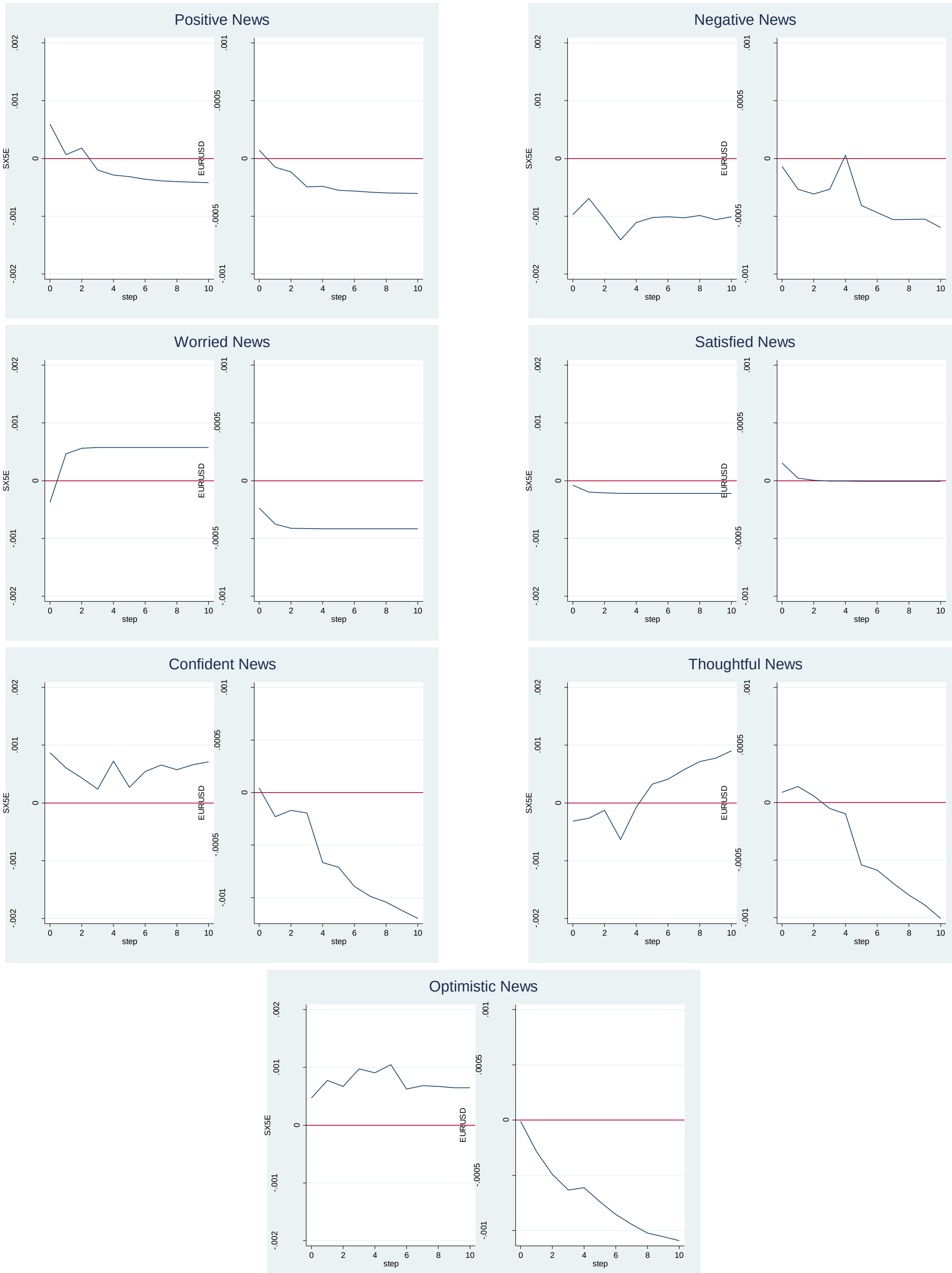

Figure 3 - EURO STOXX50 and EUR-USD – One Factor FAVAR Impulse Response Functions.

The red line denotes the y=0.

Factor-Augmented Vector Autoregressive Model - FAVAR

Even though being used very often to test economic relationships, VAR models have some shortcomings. In a world where thousands of variables affect each other, a VAR analysis usually only considers a small number of variables in order to preserve the degrees of freedom. Furthermore, the computation of the impulse response functions is constrained to the variables included in the model. Given these two reasons, and to remove endogeneity – as a result of omitted variables –, the FAVAR appears as a solution as this enables using hundreds of time series to estimate impulse response functions.

Along with the deconstruction of some puzzles found in the simple Structural Autoregressive Model, by using factors as a mean to consider unobservable factors, the FAVAR allows the computation of the Impulse Response Functions for any of the variables used in the calculation of the factors. By computing the orthogonalized Impulse Response Functions of the factors and the news sentiment with the news articles' sentiment as an impulse, and then by summing these multiplied by the coefficients of a simple regression with the variable as dependent variable and the factors as regressors (Munir and Qayyum, 2012), one can capture the reaction of the variable to changes in the news articles.

As 95% of the whole variation of the time series can be explained by only 3 factors, the FAVAR considered in the analysis will use 3 factors alongside with the observable variable s_i. The computation of the Impulse Response Functions adopts the following procedure:

$$\begin{bmatrix} F_t^1 \\ F_t^2 \\ F_t^3 \\ s_{i,t} \end{bmatrix} = \varphi(L) \begin{bmatrix} F_{t-1}^1 \\ F_{t-1}^2 \\ F_{t-1}^3 \\ s_{i,t-1} \end{bmatrix} + u_t \ (2)$$

First off one estimates the Vector Autoregressive Model given by the system of equations (2), where $s_{i,t}$ denotes the news articles sentiment variable and F_t^i each one of the factors computed using the principal analysis component.

$$y_t = \alpha + \beta_0 s_{i,t} + \beta_1 F_t^1 + \beta_2 F_t^2 + \beta_3 F_t^3 + \epsilon_t \ (3)$$

Second, (3) is estimated by ordinary least squares, where y_t portrays one of the time series' variables used to compute the factors. Even though a few regressions do not satisfy the homoscedasticity assumption, as the estimators remain still consistent and unbiased, OLS was still used. All the other Gauss Markov assumptions hold for all regressions[2].

Subsequently, from the VAR computed in (2), and given the assumption that the factors do not contemporaneously influence the sentiment and the fact that all the factors are orthogonal, four orthogonalized Impulse Response Functions are computed with an innovation shock in $s_{i,t}$ as the impulse and each factor and $s_{i,t}$ itself as the response – for simplicity, let Υ_i denote each 10-step (2 weeks) IRF.

$$\Upsilon_y = \beta_0 \Upsilon_0 + \beta_0 \Upsilon_1 + \beta_0 \Upsilon_2 + \beta_0 \Upsilon_3 \ (4)$$

To compute how does the variable y_t respond to impulses in the news sentiment $s_{i,t}$, the impulse response functions – with $s_{i,t}$ as impulse – are summed, weighted of the coefficients from the OLS regression (4).

Following the methodology presented, the impulse response functions for EURO STOXX® 50, EUR-USD exchange rate, EURO STOXX® Optimized Technology, 2-year German Bonds and

[2] Given the financial nature of the time series, no serial correlation is expected. The no serial correlation assumption was successfully confirmed using standard first-order (Durbin-Watson) and higher-order (Breusch-Godfrey and Ljung-Box) tests.

EURO STOXX 50® Volatility were computed for each sentiment as an impulse. The impulse response functions are presented in Figures 1 to 7 of the Appendix.

Succeeding the Structural Autoregressive analyses, the impact on the EURO STOXX 50® from impulses in the news sentiments was considered. The three factor FAVAR seems to solve the puzzle found regarding the worried news, which according to the previous models seemed to imply a positive impact in the returns of the stock markets. The presented model enables achieving the conclusions that if the Central Bank transmits positive, confident or optimistic signals to the economy – which then are converted into news articles -, the stock markets are going to react positively with an immediate on average boost of the stock returns of 5, 7.5 and 4 basis points respectively. On the other hand, the returns of the stock markets seem to shrink when negative, worried, thoughtful and satisfied news are sent to the market. Even though it might seem puzzling that satisfied news articles seem to drop off market returns, the comfort transmitted by the Central Bank may cause inertia from the investors, that may reduce the returns.

In what concerns the exchange rate, the results become clearer in the three-factor approach. Except for the response to "positive news", that using the 3-FAVAR yields different results from the SVAR with one factor, displaying an appreciation of the currency for the 10-weekdays after the shock of 0.25 basis points, all the other shocks feature similar impacts to the ones found in the SVAR with one factor. In fact, the transmission of positive and satisfied sentiments to the economy by the Central Bank can be interpreted as expected high economic growth, future higher interest rates or even higher competitivity by Eurozone's goods and services, that cause an appreciation of the Euro.

Despite being able to deconstruct some puzzles present in the Structural Vector Autoregressive analysis, the usage of the model presented by Bernanke et al. also comes with unexpected conclusions. In this model the technologic stocks seem to respond in the same manner regardless of the impulse given by the Central Bank.

Being able to invest at a risk-free rate is a very important feature for and of the financial markets. By affecting not only the macro decisions but also the micro ones – as the risk free is used in almost all corporate finance models – the rate of return of safe bonds, such as the German bonds must be considered by the ECB when taking decisions. In this analysis the 2-year German bonds were considered, and one is able to infer that positive, confident and optimistic cause, on average, a corresponding instantaneous increase of 5, 3.5 and 1 basis points in the 2-year risk free rate. Au contraire, negative, worried, satisfied and thoughtful news articles sentiments appear to decrease the 2-year rate.

From affecting option premia to being able to affect risk-taking strategies in the stock market, a market's volatility is a wide-broad used and studied financial variable. To measure the expected volatility of markets, some exchanges designed indices that track this parameter. A very common index used to path the volatility in Europe is the EURO STOXX 50® Volatility based on the EURO STOXX 50®. According to the applied model, besides implying higher returns of the overall stock markets, positive, confident and optimistic sentiments appear to imply a decrease in the market expectations of volatility, which may reflect increasing returns with a lower level of risk. Furthermore, worried and thoughtful revelations also reduce expected volatility. On the other hand, paired with a shrinking stock market returns, negative and satisfied news suggest higher future volatility. Whilst a negative sentiment may increase the willingness to quickly trade and sell securities and then increase the volatility, satisfied news, on paper, should calm down the markets and therefore reduce volatility, which is not verified by the model.

CONCLUSION

Financial markets are one of the busiest markets in the world and traders, as well as consultants and, most recently, computers, need to consider hundreds of different information when taking a split-second decision on whether to bid or ask a higher or lower price. Not only they need to consider all the data, but at the same time market participants affect hundreds of interconnected markets which may influence the same data. Even though being very useful at describing economic relationships, regular and commonly used econometric models, such as the Structural Autoregressive Model, lack the possibility of considering a very large number of variables, without hurting the degrees of freedom. Given this, the Factor-Augmented Vector Autoregressive model appears to solve most of these problems, especially when looking at the financial markets.

While financial markets move up and down, Central Banks analyze all the macroeconomic and financial data to make the best decisions to ensure price stability in the area, and send to the economy signals – either through monetary policy decisions, press conferences or, in some cases, through simple comments in some interviews – to affect the economy and achieve this goal.

Using the Kanjoya's lexicon to measure the sentiments perceived by the market from positions either of the European Central Bank or Mario Draghi, a measure for each sentiment was created and then used as impulse to measure the impact of this in the markets. Initially a SVAR was considered and some puzzles were found as positive news seemed to cause an ambiguous effect in the European stock market or worried ones appeared to cause stock returns to increase. These unexpected results appear to dissipate once factors created using the principal component analysis and dozens of time series were added to the model to create a FAVAR.

With the model built we found some appealing results such as the different impacts of positive and negative signals from the European Central Bank both on the returns and expected volatility of the European stock market – in which positive news seem to improve the returns of the market and decrease expected volatility, having negative news the opposite effect. Furthermore, using seven sentiments as impulses to analyze the effect in five variables, interesting results were found, especially for one of the first analyses made in this field.

Artificial intelligence and machine learning have been substantially developed in the past few years and enable a deeper analysis especially concerning sentiment analysis. We believe it is important to come up with studies to avail the developments in these areas and to continue to analyze the impact of signals from Central Banks in financial markets.

APPENDIX

Emotion	Associated Words
negative	wrong, problem, difficult, weak, worst, disturbing, concerned, terrible, disappointing, bad
positive	steady, strong, successful, nice, excellent, glad, outstanding, tremendous, healthy, helpful
worried	worried, concerned, afraid, nervous, scared, anxious, dangerous, careful
satisfied	comfortable, impressed, satisfied, content, calm, delighted, pleased, steady, stable
confident	determined, successful, accomplish, confident, achieve, strong, forward, progress
thoughtful	question, wonder, curious, interesting, consider, explore, decision
optmistic	optimistic, potential, stronger, future, expectations, confident, growth

Table 1-Most Common Words Associated with Selected Emotions (from Kanjoya Lexicon)

Akaike Information Criteria

Lag	Positive	Negative	Worried	Satisfied	Confident	Thoughtful	Optimistic
0	-12.3114	-12.7307	-14.3387	-13.2507	-12.4924	-13.2657	-12.3055
1	-12.3527	-12.8	**-14.3511***	-13.301	-12.5178	-13.3388	-12.3868
2	-12.3573	-12.8001	-14.3356	-13.3017	-12.5156	-13.37	-12.4116
3	-12.3696	-12.8064	-14.333	-13.3061	-12.522	-13.3942	-12.4149
4	-12.3683	-12.8082	-14.327	-13.3059	-12.5212	-13.3941	-12.4159
5	-12.3736	-12.8302	-14.3284	**-13.3178***	**-12.5328***	**-13.4233***	-12.4261
6	**-12.3752***	-12.8251	-14.3144	-13.3112	-12.5313	-13.4183	**-12.4285***
7	-12.3651	**-12.8316***	-14.3065	-13.3089	-12.5265	-13.4158	-12.427
8	-12.3502	-12.8142	-14.2943	-13.2937	-12.511	-13.4001	-12.4113
9	-12.3432	-12.8229	-14.2874	-13.2963	-12.5006	-13.3909	-12.4037
10	-12.3446	-12.8228	-14.2897	-13.302	-12.5044	-13.3901	-12.4147

Table 1 - Akaike Information Criteria for each sentiment

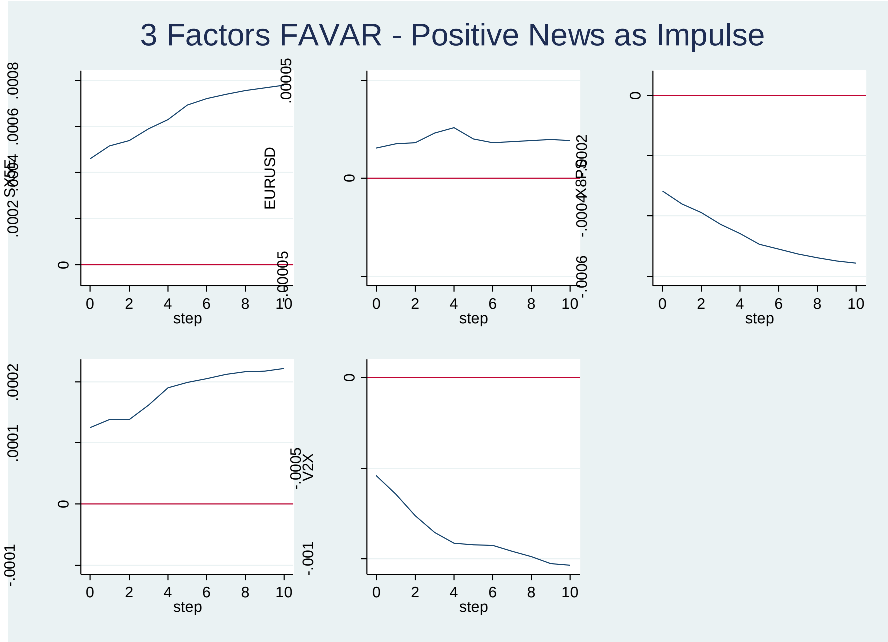

Figure 1 - 3 Factors FAVAR - Positive News as Impulse. The red line denotes the y=0. Due to the complexity of computations, no confidence bands were considered.

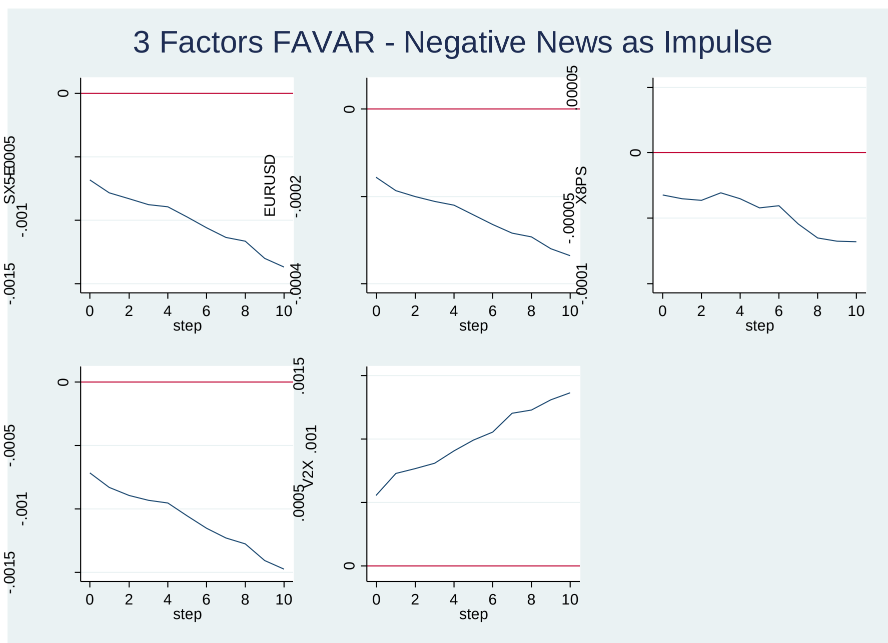

Figure 2 - 3 Factors FAVAR - Negative News as Impulse. The red line denotes the y=0. Due to the complexity of computations, no confidence bands were considered.

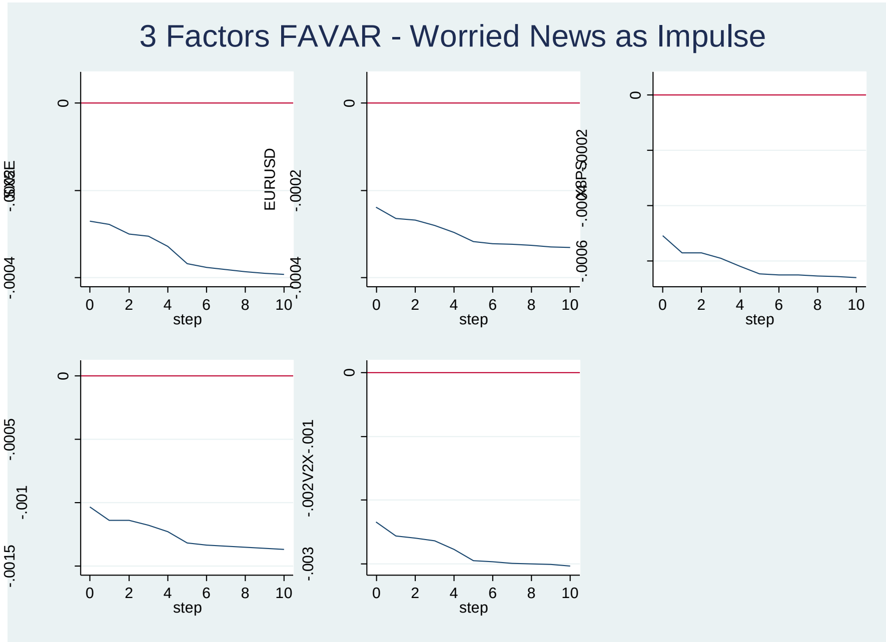

Figure 3 - 3 Factors FAVAR - Worried News as Impulse. The red line denotes the y=0. Due to the complexity of computations, no confidence bands were considered.

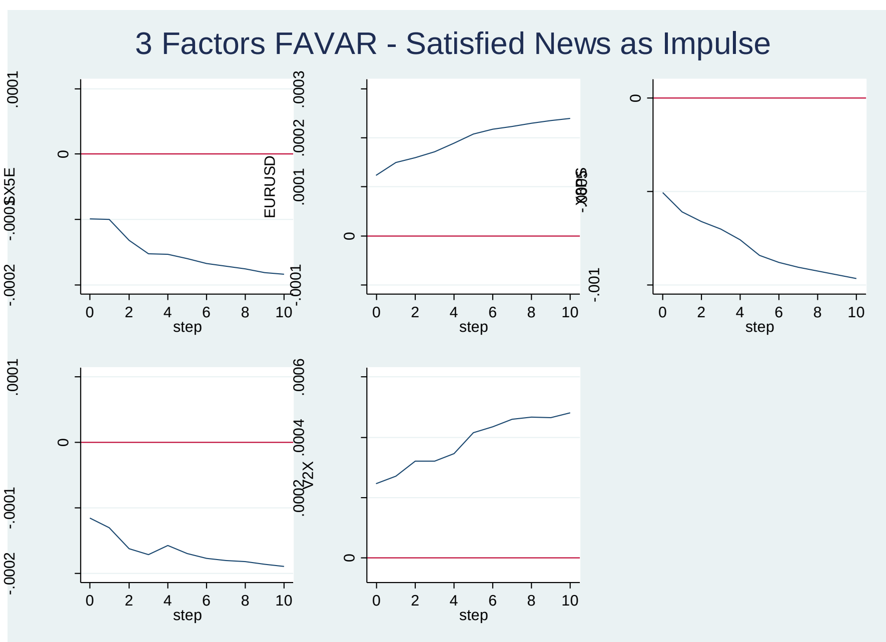

Figure 4 - 3 Factors FAVAR - Satisfied News as Impulse. The red line denotes the y=0. Due to the complexity of computations, no confidence bands were considered.

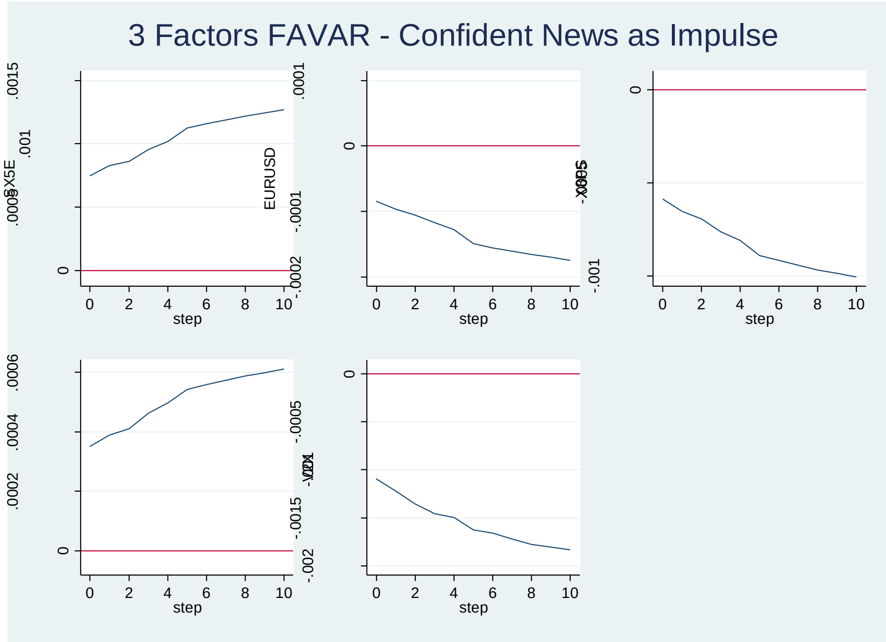

Figure 5 - 3 Factors FAVAR - Confident News as Impulse. The red line denotes the y=0. Due to the complexity of computations, no confidence bands were considered.

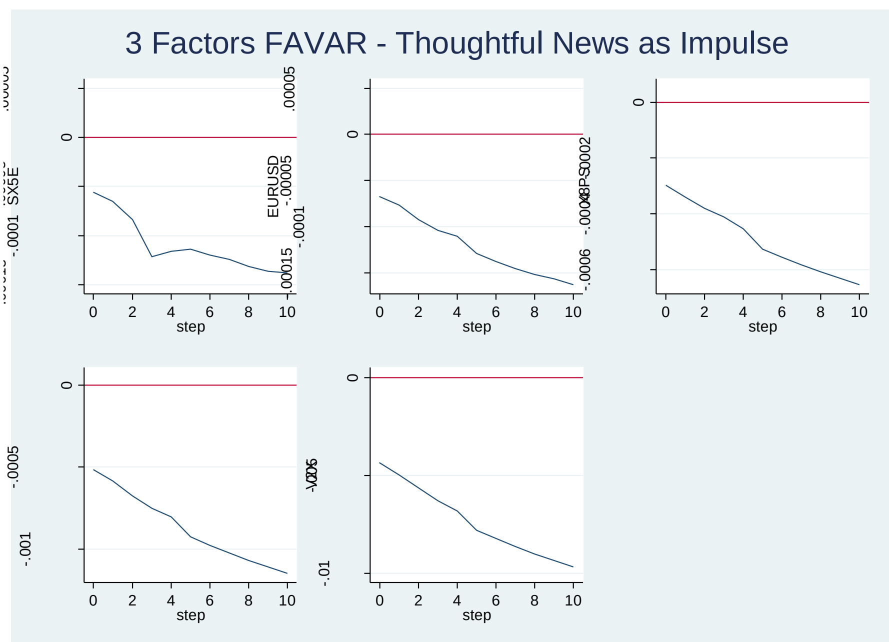

Figure 6 - 3 Factors FAVAR – Thoughtful News as Impulse. The red line denotes the y=0. Due to the complexity of computations, no confidence bands were considered.

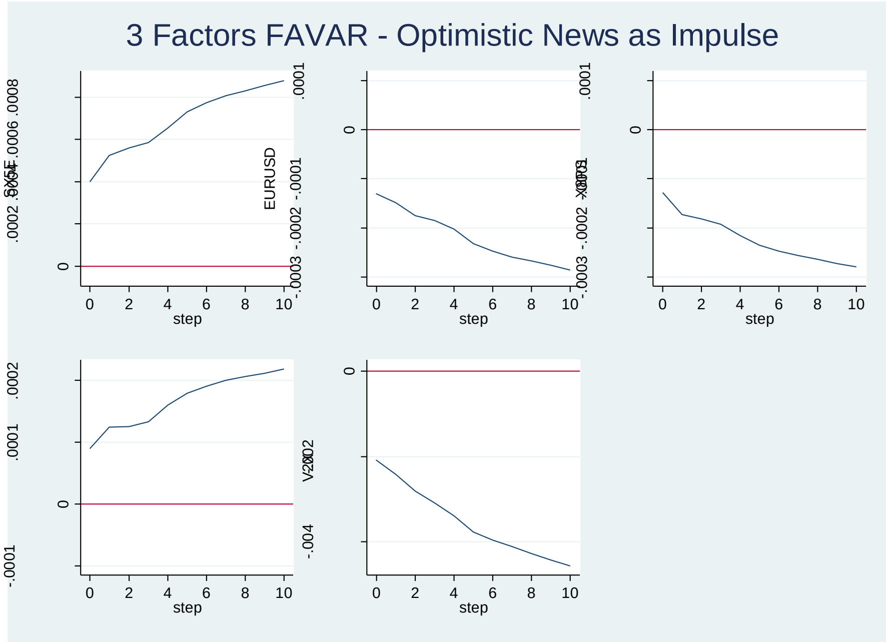

Figure 7 - 3 Factors FAVAR - Optimistic News as Impulse. The red line denotes the y=0. Due to the complexity of computations, no confidence bands were considered.

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